The Effect of Uncertainty on UK Investment Authorisation: Pooled Estimators vs. Heterogeneous Estimators[1]

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Abstract:

This paper compares pooled models of capital investment with non-pooled models using the UK's Confederation of British Industry's (CBI) Industrial Trends Survey for the U.K., particularly focusing on the effect of uncertainty on investment. The uncertainty measure is based on the cross sectional dispersion of expectations. The panel data estimation shows that uncertainty has negative effects, which are non-negligible in terms of magnitude, on investment. However, if we look at the estimation results at the industry level, we find a great diversity in elasticity and *t*-statistics, providing valuable information not available from the pooled model. Finally, we compare forecast performances based on the above models. It is confirmed that pooled estimators are generally better than non-pooled estimators in terms of forecast performance, but the difference between the two is not very large.

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1. Introduction

The panel data estimation technique, which depends on ‘pooling’ the cross-sectional element of a time-series, has been widely used in much empirical analysis. However, it is not entirely clear whether pooling is justified when parameters of time-series regression at the individual level vary considerably across samples. Some papers have questioned the homogeneity assumption and have shown that heterogeneous estimators are less biased than the traditional homogeneous estimators (*e.g.*, Robertson and Symons, 1992 and Pesaran and Smith, 1995). However, recent case studies, based on demand for gasoline (Baltagi and Griffin 1997), and cigarettes (Baltagi, Griffin, and Xiong 2000) conclude that panel estimators are better than the heterogeneous counterparts based on the individual data[2] in terms of their forecasting performance in a simple practical test.

The present study addresses the same question (whether to pool or not), empirically. This is done in the context of a model of capital investment under uncertainty. There is now a large literature on possible channels of influence form uncertainty to investment (McDonald and Siegel, 1986, Dixit and Pindyck, 1994; see also Driver and Temple eds 1999). The sign of this effect is uncertain theoretically, even in the context of real option models, but a preponderance of empirical studies have obtained a negative effect (Ferderer 1993, Ghosal and Loungani 2000, Carruth *et al.* 2000).

Our study uses the long-run quarterly data constructed by the CBI (Confederation of

[2] In these studies, two kinds of heterogeneous estimators are used- the Pesaran-Smith average estimator (Pesaran and Smith, 1995) where the parameters are averaged across states and the shrinkage estimator (Maddala, Srivastaka, and Hao, 1994, cited by Baltagi *et. al.*, 2000) in which one shrinks the individual estimates towards the pooled estimate using weights depending on their corresponding variance-covariance matrices.

British Industry) and publicly available in its *Industrial Trends Survey*. Three issues are explored. First, we investigate the role of uncertainty in investment decisions at the industry level based on both homogeneous and heterogeneous estimators. As a measure of uncertainty we used an entropy measure characterised by the diversity in the degree of being 'more' or 'less' optimistic about the general business situation (Driver and Moreton, 1992). Second, we examine the effects of pooling by comparing parameters and *t*-values on coefficients of variables in panel data models with those in the heterogeneous models. For instance, in the case where uncertainty has a negative and significant impact on investment authorisation, it is not entirely clear whether there are only a small number of industries with a negative and 'highly' significant coefficient on uncertainty. Third, drawing upon Baltagi and Griffin (1997) and Baltagi, Griffin, and Xiong (2000), we compare the forecasting performance of heterogeneous estimators and homogeneous estimators. We examine the accuracy of out of sample forecasts (for the period 1996-Q2 to 1999-Q1) based on data truncated at a cut-off point (1978-Q1 to 1996-Q1). Performance measures for the out-of-sample forecasts are derived on the basis of the root mean square errors (RMSEs) calculated for the last three years at the industry level and then averaged across industries.

The rest of the paper is organised as follows. In the next Section, we briefly outline the model specification, together with the definitions of variables and the nature of the data set. The estimation results at the industry level, based on OLS and SUR estimations, are reported in Section 3. Then, in Section 4, the panel data estimation is compared with its heterogeneous counterpart. Section 5 shows the results on the comparison of forecast performance. Section 6 concludes.

2. The Data and the Model Specification

2.1 The Data

All our data comes from the survey questions designed by the Confederation of British Industry (henceforth CBI)[3]. This survey has an excellent reputation, having been run continuously since 1958. It feeds into the EU official data series and it is regularly used in academic studies. The sample size is large with more than 1500 returns quarterly, broken down into nine major sectors and forty-eight industries.

All the data are qualitative and based on simple responses, such as 'up', down', or 'same' regarding the trend in the economic variables. It is therefore typically necessary for researchers to transform the qualitative data into quantitative data. One common approach is to use the 'balance' statistic which is the percentage of respondents replying 'up' less those replying 'down' (Junankar, 1989, see also Appendix 1 in this paper for further discussions). This transformation is most useful when the underlying data is not highly trended, as is the case for our sample questions[4].

The data are published quarterly and, at least in principle, are seasonally adjusted. The quarterly frequency is important for our purpose of investigating the role of uncertainty in investment decision, because a great degree of uncertainty is likely to arise from the unanticipated component of the short-term fluctuations in economic trend. The

[3] The questions used in the survey as well as some discussions on the CBI data are reported in Appendix 1.

[4] Some support for the use of the balance statistics may be found in Smith and McAleer (1995) and in a companion paper (Driver and Urga, 2002), using the same data set. It may be shown that company-level responses are preserved under aggregation if certain plausible assumptions are made (Driver and Meade 2001)

wording of the survey questions we use has not been changed for a long time, which enables us to construct the long-run data starting from 1978 Q 1 to 1999 Q1.[5]

2.2 Model Specification: Investment Intention Specifications

The specification that we employ is an extended form of Driver and Moreton (1992, Chap. 8). As in Driver and Moreton, our investment equations draw upon a common specification with an augmented flexible accelerator derived as an optimal response to adjustment costs. In our accelerator specification, we include uncertainty variables along with a set of other relevant variables to investigate the effect of uncertainty on investment authorisation.[6]

We specify a log-linear accelerator equation linking investment intentions, or authorisations, (A_t) to output change (ΔY_t) as:

$$\Delta \log(A)_t = b_0 + b_1 \Delta \log(\Delta Y_t) + ECT_{t-1} + e_t \qquad (1)$$

where ECT_{t-1} is an error correction term specified on the assumption that A and (ΔY) may be non-stationary and e_t is an error term.

Both of the right hand side terms in (1) need to be constructed from the available data. Using a Taylor expansion we note that $\Delta \log(\Delta Y)_t$ may be proxied as follows:

$$\Delta \log(\Delta Y)_t = \Delta \log(Y)_t + \Delta\Delta \log(Y)_t \qquad (2)$$

[5] Though the survey was first published in 1958, our data set covers the period 1978 Q1 to 1999 Q1, since the question on authorisation of investment was added in 1978.

[6] The use of investment authorisation has the merit of shortening the lag structure (Driver and Moreton, 1992).

Using the survey balances of "up" responses minus "down" responses to proxy growth rates (see Smith and McAleer 1995), this may be written as:

$$Auth_t = b_0 + b_1[BAL(Y) + \Delta BAL(Y)]_t + ECT_{t-1} + e_t \qquad (3)$$

where $Auth_t$ is, as in the text, the balance statistics for plant and machinery investment authorisation and BAL(Y) represents the balance statistic for output.

The error correction term ECT_{t-1} represents, from (1), the deviation of authorisations or investments from the target level that depends on (ΔY). Identifying investment as an increment of capital and expressing capital in terms of potential output Y*, ECT_{t-1} may be written as $\log(\Delta Y^* / \Delta Y)_{t-1}$. Using a Taylor expansion this term may be expressed as

$$\log(Y^* / Y)_{t-1} - \Delta \log(Y / Y^*)_{t-1} = -[\log CU + \Delta \log(CU)]_{t-1} \qquad (4)$$

where CU_t is the percentage of firms reporting capacity utilisation above normal (% answering "NO" to CBI question 4).

Thus, the final specification is:

$$Auth_t = b_0 + b_1 yterm_t + b_2 cuterm_{t-1} + e_t \qquad (5)$$

where $yterm_t$ and $cuterm_{t-1}$ are the square bracketed terms in (3) and (4) respectively, and where the sign on b_2 is expected to be positive. (5) is the equation which can be directly estimated by the CBI survey data. To obtain the reduced form of the estimated equation, we further assume that investment authorisation is affected by the lagged authorisation $(Auth_{t-1})$, by the measure of being optimistic about the general business situation (opt_t), by the degree of uncertainty (unc_t), and by the current value of the differenced log terms in capacity utilisation $(dlcu_t)$[7]. Since the CBI survey has two kinds of information on output, that is the forward-looking term and the backward-looking term (see Question 8 in the Appendix 1), our model includes both forward and backward terms of $yterm_t$, denoted by $yfterm_t$ and $ybterm_t$ respectively. We include only the current value of $yfterm_t$ and both the current and lagged values of $ybterm$ in our specification.

The reduced form of the equation which we will estimate throughout the paper is:

$$Auth_{it} = b_{i,0} + b_1 Auth_{i,t-j} + b_2 opt_{it} + b_3 yfterm_{i,t} + b_4 ybterm_{i,t} + b_5 ybterm_{i,t-1} + b_6 cuterm_{i,t-1} + b_7 unc_{i,t-j} + b_8 dlcu_{i,t} + e_{i,t} \tag{6}$$

where Auth $_{it}$ is the rate of change of authorisation as proxied by the CBI balance statistics for the i^{th} industry at time t (where i denotes the number of industry corresponding to the industry number in the CBI survey; i = 22, 23,…., 70, and t denotes time corresponding to the quarterly data, that is, t = 1 for 1978 Q1, t = 2 for 1978 Q1,…., t = 85 for 1999 Q1).

2.3 The Measure of Uncertainty

The measure of uncertaitny we use in this paper is based on the dispersion of beliefs across survey respondents about the general business situation in their *industry*. Specifically, we use an entropy measure defined as:

[7] The optimism measures capture both interest rate and exchange rate effects, while the differenced term utilisation captures additional dynamic effects.

$$UNC_{it} = \sum_{j=1}^{3} [S_{jt} \log S_{jt}] \tag{7}$$

where S_{jt} is the share of each of the three reply categories ('up', 'down' and 'same') in Question 1 on the degree of being 'more' or 'less' optimistic about the general business situation compared with the situation four months ago (see the Appendix 1 for more detailed discussion). When the answer are equally divided, UNC reaches its maximum of three. As the actual firm data are kept confidential, there is no other means of assessing the dispersion across firms in each industry (Driver and Moreton, 1992). The constructed entropy variable has however been used successfully in other contexts involving surveys with three possible replies to measure the extent of disagreement among respondents (Fuchs, Krueger and Poterba, 1998). The measure is used by the IMF as an index of forecasting uncertainty and has been used in studies of investment under uncertainty e.g. Ferderer (1993), Driver and Moreton (1991).

Most researchers tend to equate uncertainty with conditional volatility of some key variable on the grounds that the underlying stochastic process is ergodic so that the cross-section distribution of outcomes at future points in time is captured by the (conditional) time-series distribution. The theoretical justification for the dispersion measure is that it provides a direct representation of the underlying uncertainty at a particular time horizon. It thus provides the same information but in a more direct way as does an index of conditional volatility.

One criticism of the use of consensus measures to capture uncertainty is that consensus relates to the distribution of individual means and this distribution may differ from the distribution of an individual about their mean. For example there may be a clustering together of mean forecasts with no reduction in the individual variances. However, empirical research using the US Livingstone Data and NBER Survey data have confirmed that measures of uncertainty and consensus are positively correlated (Bomberger and Frazer, 1981; Zarnowitz and Lambros, 1987; Bomberger, 1996 and 1999).

3. Empirical results

3.1 Heterogeneous Estimators

In this section, we first focus on OLS estimation at industry level where equation (6) is applied to data on each industry. To allow for the possibility that the error term is contemporaneously correlated across industries, the unrestricted seemingly unrelated regression (SUR) method is also applied.

3.1.1 OLS estimates

Table 1 reports column (i), for each industry, the elasticity evaluated at means (rather than coefficient) and t-values are presented to evaluate the relative importance of uncertainty in the decision of investment authorisation[8].

[Insert Table 1 somewhere here]

The coefficients (as well as the measures of elasticity) on uncertainty are negative and significant for five industries, namely, 37 (agricultural machinery), 45 (office machinery and data processing equipment), 48 (electrical consumer goods), 55 (Drink

[8] We do not report in this paper the full set of results based on OLS and SURE at the industry level. However, they are available on request.

and Tobacco), and 69 (Rubber products)[9] among the total of 48 industries. These industries show a relatively high elasticity of uncertainty on investment. For example, in Rubber products, if the entropy increases 1 percent, investment authorisation is estimated to decrease by 13.76 percent. However, the mean elasticity is around zero, while there is great diversity in the elasticity of uncertainty on investment.

3.1.2 SURE estimates

The above estimations based on the OLS assume that there are no cross-equation correlations among error terms. This is not the case if the industries within a sector are affected by the same shock that is not fully captured by the model. Therefore, it is interesting to apply to the same data the unrestricted SURE model which takes account of the contemporaneous covariances among error terms[10]. Breusch and Pagan (1980) tests are carried out to examine the hypothesis that individual equations are independent in SURE models. The use of SURE is justified as the hypothesis of independence is rejected at 10% level in all three cases: $\chi^2_{703} = 751.774$ (p-value=0.0986).

Column (ii) in Table 1 shows the results on unrestricted SURE where *unc* (based on entropy measure) is included. The industries with negative and significant coefficients (or elasticities) associated with *unc* are the industry 30, Pharmaceuticals and consumer chemicals, (t-value -2.23), 35 Constructional Steel Work (t value -1.93), 37 Agricultural

[9] We use the same numbering of industries as in the CBI Survey.

[10] Since there are several industries with missing observations (22, 23, 29, 34, 45, 48, 49, 51, and 62), the total number of industries is reduced to 37 in the SURE estimations.

Machinery (t value -3.89), 55 Drink and Tobacco (t-value -1.81) and 66 Pulp, paper and board (t-value -2.27) and 69 Rubber Products (t-value -3.91). While this supports our results based on OLS, it must be noted that there are three additional industries (30, 35 and 66) in which negative and significant correlation between uncertainty and authorisation of investment is not found in the case of OLS. Industries with positive and significant coefficients for *unc* are 28, 39 and 42.

In sum, the average of heterogeneous estimators show that coefficients and elasticity of uncertainty measures on investment authorisation is around zero. However, this 'average' estimator hides a great deal of diversity in estimates across industries. In particular, we have noted that there are several industries in which uncertainty plays a significant role in investment authorisation. For these industries, the 'magnitude' of the role of uncertainty in determining investment authorisation is non-negligible. The next question then to investigate is to what extent the pooled regression reflects the diversity at the individual industry level. We will compare the heterogeneous regression with the homogeneous counterpart in the next section.

3.2 Homogeneous Estimators

3.2.1 Panel and SURE Estimations

In order to see the effects of pooling the micro data (*i.e.*, the industry level data), we will compare two cases, namely (A) the case where all industries are pooled and (B) the case where industries with negative and significant coefficients on uncertainty are not included. Though we tried four different specifications (1. the case without time or industry dummy variables; 2. the case with time dummies[11]; 3. the case with industry dummies[12] and 4. the case with both) we report only the results for the model 4., including both time and industry (sector) dummies, because the four cases show similar estimation results. We report the results of both fixed-effects and random-effects together with two types of specification tests, *i.e.*, Hausman Tests and Breusch and Pagan Tests. Our a-priori view is in favor of fixed effects since we sample the full set of industries in UK manufacturing.

Because of space limitations we have until now presented only coefficients on uncertainty. For the panel results, however, we present the full set of estimates corresponding to the specification in equation (6). A number of interesting results are reported below in Table 2.

[Insert Table 2 somewhere here]

Case A in Table 2 reports the panel estimation based on all industries. This is contrasted in case B with estimation results based on the sample *omitting* the five industries where *unc* negatively and significantly affects investment authorisation. It is notable that in A the coefficient (or elasticity) on *unc* is negatively significant, whilst in B it is positive and insignificant. That is, industries with negative and significant coefficients on *unc*

[11] Time dummies are on the quarterly basis. For example, t1 takes 1 if sample is of 1978Q1, 0 otherwise. Likewise, t2 denotes1978Q2, ….., and t85 denotes 1999Q1.

[12] Industry dummies are based on ten broad categories of industries found in the CBI survey. For example, I1 takes 1 if industry is Food, Drink and Tobacco and 0 otherwise. Likewise, I2=Chemicals, I3=Metal Manufacture, I4=Textiles, I5= Mechanical Engineering, I6= Electrical and instrument engineering, I7= Metal Products, I8= Paper Printing and Publishing, and I9= Motor vehicles and other transport equipment.

are responsible for the corresponding negative and significant coefficients on the panel regressions[13]

Table 2 (case C) also reports the case where all coefficients are set to be equal in the restricted SURE estimator. Again we observe a negative and significant association of uncertainty with authorization.

3.3 Forecast Comparisons

How can our different estimators be compared? In this section we focus on a simple practical test of the different estimators, particularly focusing on 1) the difference between heterogeneous estimators and homogeneous estimators and 2) the diversity among different industries[14]. Our procedure is summarised as follows.

(1) Estimate all the models in the last two sections for the case where *unc* (entropy measure) is used as one of the explanatory variables, retaining the last 12 quarters of data for forecast performance tests.

(2) calculate RMSEs (the root mean square errors) using the actual values of investment authorisation and the predicted values

(3) average RMSEs across industries.

Table 3 reports the full set of RMSE results for non- pooled (cases a and b), pooled (casesc,d,e) and SURE estimations (cases f,g, and h).

[13] This confirms the underlying heterogeneity of the uncertainty coefficient in investment equations noted by other researchers. Whereas aggregate investment functions disguise the heterogeneity and generally indicate negative coefficients, disaggregated studies have included results with positive as well as negative signs (Carruth et al. 2000).

[14] We follow here the methodology in Baltagi and Griffin (1997) and Baltagi, Griffin, and Xiong (2000). Again due to space considerations we only report the uncertainty elasticities. See also West and Cho (1995) who pursue similar objectives of company forecasting performance across models in the context of univariate conditional variance with high frequency data.

[Insert Table 3 somewhere here]

The last two rows in Table 3 give RMSE statistics averaged across industries and their rankings. These indicators show that pooled estimators are generally better than estimators based on both non-pooled samples and SURE. As in Baltagi and Griffin (1997) and Baltagi, Griffin, and Xiong (2000), the key conclusion of our paper is that the pooled model outperforms the non-pooled models and SURE. The restricted SURE (case f) which is the closest specification to the pooled one ranks in performance, way ahead of the unrestricted SURE (case g) or the SURE specification with restricted error correction terms (the pooled mean group estimator – case h). The fact that the restricted SURE outperforms the unrestricted SURE occurs despite a clear rejection of the restrictions in the likelihood ratios tests. For case f versus case g, $\chi^2_{296} = 579$, clearly rejecting the restrictions. The same is true for case h versus case h with $\chi^2_{37} = 74$.

Summary and Conclusion.

In this study we have compared pooled and non-pooled models of investment. A standard industry-level error-correction specification was augmented with terms in business optimism and uncertainty using data from the CBI's Industrial Trends Survey running over the period 1978Q1 till 1999Q1. Our uncertainty (entropy) measure is based on the cross sectional dispersion of expectations. Three different sets of estimation methods were used: single equation, panel, and SURE

We first report conclusions in respect of the investment model. Irrespective of the estimation method used a strong effect from uncertainty to investment is obtained in all specifications.

Focusing now on the panel data estimates, these also show that uncertainty has negative effects on investment authorisation. This is an important piece of empirical evidence supporting those theories such as real options that predicts this effect. Furthermore, the elasticity of uncertainty on investment authorisation is non-negligible (-1 to –3) compared with other factors (e.g., the measure of being optimistic which is 0.9).

Our next conclusion focuses on the robustness of the panel estimates. At industry level, we find great diversity in terms of elasticity and *t*-statistics. Therefore, we performed separate panel data estimation for the full set of industries, and for the set which excludes industries in which investment authorisation is significantly and negatively affected by the entropy measure of uncertainty. Only in the former does uncertainty have a negative and significant effect on investment authorisation, while the remaining coefficients are virtually identical in both sets of results. This supports the hypothesis that the results of the pooled model are affected by a relatively small number of industries with negative and highly significant coefficients on uncertainty. Clearly it would therefore be possible to misinterpret panel evidence as having general applicability when it applies only to a small subset of the total. This finding underscores the importance of complementary estimation methods. Given the long-run data, it is clearly useful also to apply OLS and SURE at industry level.

SURE models are relevant because of the possibility that error terms at the industry level are contemporaneously correlated. This could arise, for example, due to the omission of common tax effects in our specification. Standard tests reject the hypothesis that individual equations are independent at 10 percent level of significance, which supports the use of SURE. Restricted SURE (where all the coefficients, except constant, are assumed to be equal) produces results broadly similar to the pooled results derived by fixed- or random-effects estimations, though these restrictions are heavily rejected by the data.

Finally, we compare forecast performances based on the different estimation methods, drawing upon the methodology put forward by Baltagi and Griffin (1997) and Baltagi, Griffin, and Xiong (2000). Using the data truncated at the first quarter in 1996, the out-of-sample forecasts are calculated based on RMSEs (Root Mean Square Errors) for the last twelve quarters (1996 Q2 to 1999 Q2) at the industry level. The industry-level estimation is averaged across industries to compare the forecast performance of heterogeneous estimators and the homogeneous counterparts.

The results of these comparisons confirm that pooled estimators are generally better than non-pooled estimators in terms of forecast performance, but the difference between the two is not very large. This implies that, while there is some merit in pooling the data, it may not outweigh the disadvantage of pooling in terms of disguising the underlying heterogeneity in the data referred to earlier.

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APPENDICES

Appendix 1   Data Sources

In this paper, we draw upon the Industrial Trends Survey carried out by the main U.K. employers organisation, the Confederation of British Industry.   It has been published on a regular basis since 1958 and has been widely used by economists. However, our panel data set covers the period 1978 Q1 to 1999 Q1, since the question on authorisation of investment was added in 1978.   The responses in the survey are weighted by net output with the weights being regularly updated.   The survey sample is chosen to be representative and is not confined to CBI members

Survey Questions
CBI Industrial Trends Survey Questions
Question 1
Are you more, or less, optimistic than you were four months ago about the general business situation in your industry?

Ques*tion 3b*
Do you expect to authorise more or less capital expenditure in the next twelve months than you authorised in the past twelve months on: plant and machinery? (Possible Choices: ‘More’, ‘Same’ or ‘Less’)

Ques*tion 4*
Is your present level of output below capacity (i.e., are you working below a satisfactory full rate of operation)? (‘Yes’, or ‘No’)

Question 8
Excluding seasonal variations, what has been the trend over the PAST FOUR MONTHS, and what are the expected trends for the NEXT FOUR MONTHS, with regard to: Volume of output?   (‘Up’, ‘Same’ or ‘Down’)

Appendix 2 IV Estimates [a]: Dep. Variable, Authorisation of Plant and Machinery based on CBI survey (unc: entropy measure is used)

Endogenous Variables: Opt, Yfterm, Unc, Dlcu

Instruments: Opt(-1), Opt(-2), unc(-1), unc(-2), Dlcu(-1), Dlcu(-2), Yfterm(-1)

Industry	*Auth_1*	(t-value) [b]	*Opt*	(t-value)	*Yfterm*	(t-value)	*Ybterm*	(t-value)	*Ybterm_1*	(t-value)	*Cuterm_1*	(t-value)	*unc*	(t-value)
all industries (panel)	0.43	(28.03) **	0.32	(8.27) **	0.08	(2.60) **	0.03	(2.05) *	0.04	(-3.44) **	6.33	(2.61) **	-11.74	(-0.83)
22	0.80	(4.04) **	-0.87	(-0.95)	0.23	(0.61)	0.31	(1.74) +	0.17	(-0.96)	0.47	(0.03)	-15.62	(-0.12)
23	0.38	(1.36)	0.42	(0.91)	0.02	(0.07)	0.05	(0.19)	0.19	(-0.94)	5.96	(0.14)	389.36	(0.54)
24	0.37	(5.97) **	-0.04	(-0.13)	-0.01	(-0.08)	0.08	(1.08)	0.14	(-2.18) *	-4.74	(-0.27)	64.61	(0.37)
25	0.47	(1.03)	-1.15	(-0.47)	-1.20	(-0.51)	0.66	(0.50)	0.42	(-0.65)	-42.47	(-0.59)	-589.22	(-0.58)
26	0.24	(1.36)	0.33	(1.41)	0.16	(-1.02)	0.12	(1.53)	0.06	(-0.83)	29.66	(1.52)	227.90	(1.27)
27	0.60	(5.41) **	0.34	(1.40)	-0.05	(-0.17)	0.02	(0.16)	0.05	(-0.58)	6.62	(0.55)	89.81	(0.60)
28	0.34	(1.82) +	0.42	(1.80) +	-0.07	(-0.23)	0.04	(0.39)	-0.07	(0.76)	51.36	(1.34)	-91.36	(-0.36)
29	0.36	(1.29)	0.12	(0.39)	0.02	(0.06)	0.17	(1.97) +	0.09	(-0.95)	-10.13	(-0.25)	9.87	(0.12)
30	0.21	(1.13)	-0.29	(-0.64)	-0.25	(-0.73)	0.04	(0.28)	0.06	(-0.43)	81.07	(2.16) *	17.13	(0.14)
31	0.63	(2.50) *	1.22	(1.56)	-0.35	(-1.12)	0.17	(0.52)	0.09	(-0.35)	-27.87	(-0.87)	237.88	(0.52)
32	0.48	(2.74) **	0.41	(0.86)	0.15	(0.60)	0.02	(0.06)	0.23	(-1.49)	-19.16	(-0.69)	-198.58	(-0.97)
33	0.44	(2.65) **	0.06	(0.17)	-0.03	(-0.10)	0.20	(1.21)	0.17	(-2.55) *	-8.59	(-0.35)	-81.96	(-0.36)
34	0.53	(3.83) **	0.48	(1.24)	0.12	(0.63)	-0.05	(-0.36)	0.01	(-0.08)	-3.67	(-0.22)	-26.04	(-0.23)
35	0.29	(1.97) +	0.26	(1.12)	0.35	(1.45)	0.17	(1.92) +	0.11	(-1.34)	-14.69	(-0.49)	-185.04	(-1.29)
36	0.36	(-0.16)	0.16	(0.52)	-0.17	(0.52)	-0.43	(3.04) **	0.12	(0.31)	10.12	(1.05)	-42.59	(-1.14)
37	0.09	(0.40)	0.54	(0.73)	0.17	(0.59)	0.02	(0.10)	-0.13	(0.79)	46.17	(1.51)	-407.68	(-1.29)
38	0.25	(1.01)	0.15	(0.31)	-0.43	(-1.01)	0.35	(2.11) *	0.19	(-1.41)	-24.31	(-0.90)	349.09	(1.22)
39	0.78	(2.10) *	0.14	(0.44)	0.25	(0.76)	-0.01	(-0.10)	0.10	(-0.87)	11.54	(0.54)	-191.64	(-1.24)
40	0.20	(1.33)	0.67	(1.50)	-0.37	(-1.21)	-0.07	(-0.61)	0.16	(-1.00)	31.41	(0.59)	138.81	(0.43)
41	0.34	(2.26) *	0.31	(1.15)	-0.14	(-0.48)	0.20	(1.67) +	0.10	(-1.20)	24.95	(0.85)	180.56	(0.95)
42	0.39	(2.78) **	0.50	(1.47)	-0.28	(-0.99)	0.08	(0.67)	0.03	(-0.24)	0.25	(0.01)	-53.10	(-0.20)

43	0.23	(1.19)	0.09	(-0.26)	0.06	(0.43)	0.12	(0.90)	0.17	(-1.78) +	11.28	(0.35)	-249.75	(-1.18)

Appendix 2 IV Estimates [a]: Dep. Variable, Authorisation of Plant and Machinery based on CBI survey (unc: entropy measure is used) (continued)

Industry	*Auth_1*	(t-value) [b]	*Opt*	(t-value)	*Yfterm*	(t-value)	*Ybterm*	(t-value)	*Ybterm_1*	(t-value)	*Cuterm_1*	(t-value)	*unc*	(t-value)
44	0.29	(1.60)	0.44	(1.10)	-0.05	(-0.25)	0.05	(0.33)	0.07	(-0.67)	35.33	(1.38)	-104.73	(-0.68)
45	-1.07	(-0.55)	0.94	(0.45)	0.16	(0.20)	0.16	(0.40)	-0.10	(-0.23)	178.74	(0.64)	-732.32	(-0.61)
46	3.39	(2.23) *	0.26	(0.56)	0.22	(1.00)	-0.17	(0.72)	0.05	(-0.30)	14.47	(0.35)	-429.53	(-1.05)
47	0.24	(1.67) +	0.63	(1.36)	-0.22	(-1.48)	-0.02	(-0.16)	0.00	(0.02)	20.70	(0.91)	150.22	(1.73) +
48	0.56	(4.01) **	0.45	(1.34)	0.06	(0.45)	0.00	(0.01)	0.95	(-1.54)	-12.83	(-0.54)	29.87	(0.21)
49	0.12	(0.79)	0.48	(1.06)	0.11	(0.39)	0.12	(0.98)	0.08	(-0.88)	-5.03	(-0.16)	93.45	(0.99)
50	0.42	(3.48) **	0.23	(0.98)	0.23	(0.92)	0.03	(0.28)	0.03	(-0.49)	41.63	(1.96) +	34.80	(0.34)
51	0.29	(1.38)	0.10	(0.27)	0.16	(0.56)	0.12	(0.85)	-0.13	(1.12)	-5.43	(-0.27)	-158.45	(-0.70)
52	-1.32	(-1.31)	3.21	(1.70) +	0.54	(1.06)	-0.07	(-0.19)	0.46	(-1.18)	92.47	(1.42)	705.74	(1.27)
53	0.41	(2.72) **	0.47	(1.45)	0.21	(1.07)	0.00	(-0.04)	-0.03	(0.38)	-6.18	(-0.15)	-30.02	(-0.18)
54	0.08	(0.48)	0.47	(1.01)	0.14	(0.77)	-0.09	(-1.06)	0.02	(-0.27)	25.61	(0.43)	-13.67	(-0.13)
55	0.25	(1.66) +	-0.50	(-1.52)	-0.15	(-0.38)	0.22	(1.48)	0.01	(-0.05)	75.41	(1.85) +	-85.14	(-0.44)
56	0.29	(1.42)	0.14	(0.78)	-0.16	(-1.20)	0.03	(0.36)	0.07	(-0.83)	46.36	(1.44)	-37.43	(-0.30)
57	1.49	(3.52) **	0.24	(1.33)	0.21	(1.09)	-0.08	(-1.15)	-0.03	(0.40)	29.49	(1.27)	-142.59	(-1.34)
58	0.35	(1.92) +	0.21	(1.02)	0.25	(0.78)	0.00	(0.02)	0.10	(-0.63)	-53.35	(0.74)	-72.67	(-0.83)
59	0.20	(1.49)	0.30	(0.95)	0.15	(0.76)	-0.11	(-0.99)	-0.01	(0.06)	54.60	(1.30)	109.22	(0.56)
61	0.34	(1.99) +	0.61	(1.88) +	-0.26	(-0.93)	0.16	(1.60)	0.01	(-0.11)	29.29	(0.65)	-86.80	(-0.37)
62	0.67	(4.11) **	0.27	(0.66)	-0.10	(-0.39)	0.11	(0.71)	-0.04	(0.23)	-3.73	(-0.13)	116.99	(0.51)
63	0.25	(1.86) +	0.63	(2.08) *	-0.25	(-1.29)	-0.11	(-0.89)	0.16	(-0.20)	22.79	(0.60)	-138.10	(-0.82)
64	0.35	(1.85) +	-0.21	(-0.78)	0.17	(0.80)	0.14	(1.26)	0.21	(-2.31) *	14.38	(0.66)	226.14	(2.00) *
65	0.53	(4.07) **	0.74	(2.23) *	0.15	(0.34)	-0.13	(-0.89)	-0.72	(0.74)	1.09	(0.05)	-73.56	(-0.33)
66	0.45	(2.80) **	0.29	(0.64)	0.50	(0.97)	-0.16	(-0.59)	0.03	(-0.26)	16.56	(0.68)	-257.80	(-0.95)
67	0.33	(2.10) *	-0.15	(-0.32)	0.36	(1.67) +	0.04	(0.26)	0.05	(-0.44)	9.94	(0.37)	36.79	(0.22)
68	0.35	(2.17) *	0.41	(0.78)	-0.13	(-0.61)	0.04	(0.14)	0.23	(-0.73)	-31.27	(-0.44)	265.62	(1.78) +

69	0.32	(3.03) **	0.63	(1.62) +	-0.01	(-0.08)	-0.02	(-0.17)	0.07	(-0.96)	-2.35	(-0.10)	-38.93	(-0.41)
70	0.29	(1.48)	0.09	(0.25)	-0.03	(-0.19)	0.07	(0.57)	0.22	(-1.83) +	20.43	(0.51)	128.17	(0.67)

Appendix 2 IV Estimates [a]: Dep. Variable, Authorisation of Plant and Machinery based on CBI survey (continued)

			Specification Tests								
			Hausman Test for IV		Davidson & MacKinnon's Augmented Reg. Test						
Dlcu	(t-value)	Cons	Chi2(5)	Consistant Estimator	F(4,70)	Consistant Estimator	No. of Obs.	F test	R2	Std. Er.	Industry
-5.39	(-1.16)	-5.19	17.99 *	IV	4.72 **	IV	3734	343.43	0.43	24.94	all industries (panel)
-7.07	(-0.14)	3.96	3.25	OLS	0.53	OLS	56	3.38 **	0.04	35.93	22 Coal and petroleum product
-14.83	(-0.20)	-143.68	2.21	OLS	0.38	OLS	59	2.72 *	0.00	37.35	23 Extraction of minerals and metalliferous ores
-3.47	(-0.09)	-17.51	3.29	OLS	0.62	OLS	83	10.49 **	0.52	36.39	24 Ferrous metals
111.47	(-0.66)	241.23	5.83	OLS	0.79	OLS	83	0.55	0.00	95.31	25 Non-ferrous metals
-51.89	(-1.36)	-112.77	4.68	OLS	0.98	OLS	83	10.48 **	0.42	22.46	26 Building materials
1.79	(0.08)	-38.47	2.68	OLS	0.46	OLS	83	27.54 **	0.75	16.85	27 Glass and ceramics
-68.24	(-1.20)	-47.21	2.37	OLS	0.57	OLS	83	7.15 **	0.39	25.07	28 Industrial chemicals
19.45	(0.28)	1.66	2.96	OLS	0.55	OLS	45	1.60	0.23	31.38	29 Agricultural chemicals
-116.70	(-1.69) +	-136.59	3.98	OLS	0.11	OLS	83	3.59 *	0.23	31.38	30 Pharmaceuticals and consumer chemicals
23.79	(0.53)	-11.96	8.86	OLS	1.60	OLS	45	2.00 +	0.00	64.04	31 Man made fibres
53.45	(1.07)	108.19	10.94 *	IV	1.66	OLS	83	9.67 **	0.40	25.05	32 Foundries; and forging, pressing and stamping
50.31	(0.95)	47.72	5.58	OLS	0.61	OLS	83	18.30 **	0.64	17.06	33 Metals goods n.e.s.
14.41	(0.44)	19.92	5.96	OLS	1.20	OLS	78	12.64 **	0.58	24.42	34 Hand tools and implements
4.18	(0.07)	86.53	11.70 *	IV	1.24	OLS	83	6.17 **	0.24	21.60	35 Constructional stealwork
-5.22	(-0.43)	-7.72	3.21	OLS	0.42	OLS	83	2.34 *	0.15	26.26	36 Heavy industrial plant
-68.35	(-1.35)	58.88	7.05	OLS	2.98 *	IV	83	4.22 **	-	46.06	37 Agricultural machinery
38.69	(0.70)	-93.41	19.39 **	IV	5.55 **	IV	83	3.74 **	-	34.58	38 Metal working machine tools
-7.09	(-0.20)	49.47	6.12	OLS	0.97	OLS	83	8.51 **	0.40	23.36	39 Engineer's small tools
-66.20	(-7.20) **	-91.18	0.67	OLS	2.78	OLS	83	4.09 **	0.03	30.71	40 Industrial machinery
-60.99	(-1.18)	-108.97	2.46	OLS	0.64	OLS	83	9.06 **	0.43	25.60	41 Contracters' plant
11.21	(0.28)	26.02	4.56	OLS	1.25	OLS	83	6.27 **	0.30	25.12	42 Industrial engines, pumps and compressors

-15.59	(-0.26)	84.46	5.21	OLS	1.06	OLS	83	4.15 **	0.00	25.33	43 Heating, ventilating and refregiating equipment

Appendix 2 IV Estimates [a]: Dep. Variable, Authorisation of Plant and Machinery based on CBI survey (unc is used) (continued)

Dlcu	(t-value)	Cons	Chi2(5)	Estimator	F(4,70)	Estimator	Obs.	F test	R2	Std. Er.	Industry
-87.33	(-1.35)	-13.49	2.81	OLS	0.84	OLS	83	17.99 **	0.63	16.60	44 Other mechanical equipment
-316.08	(-0.59)	-10.92	12.33 +	IV	1.46	OLS	43	0.52	-	94.09	45 Office machinery and data processing equipment
-2.86	(-0.04)	123.97	3.95	OLS	1.06	OLS	83	2.80 **	-	37.11	46 Electrical industrial goods
-28.10	(-0.64)	-69.17	9.92 +	IV	1.66	OLS	83	4.33 **	0.21	28.97	47 Electronic industrial goods
36.56	(0.92)	19.04	2.80	OLS	1.23	OLS	72	9.38 **	0.51	32.97	48 Electrical consumer goods
36.86	(0.67)	-14.86	4.25	OLS	0.56	OLS	67	3.05 **	0.27	33.66	49 Electronic consumer goods
-94.76	(-2.11) *	-68.60	6.72	OLS	1.79	OLS	83	8.09 **	0.40	27.18	50 Motor vehicles
5.49	(0.15)	28.93	0.87	OLS	0.18	OLS	42	0.85 **	0.09	44.29	51 Shipbuilding
-195.72	(-1.46)	-308.67	2.13	OLS	0.52	OLS	83	0.95 **	-	120.98	52 Aerospace and other vehicles
2.17	(0.03)	22.58	6.54	OLS	1.70	OLS	83	4.66 **	0.16	26.45	53 Instrument engineering
-50.76	(-0.47)	-29.22	4.93	OLS	1.25	OLS	83	3.00 **	0.19	18.68	54 Food
-153.26	(-1.94) +	-104.52	1.08	OLS	4.01 **	IV	83	3.15 **	-	34.18	55 Drink and Tabacco
-37.38	(-0.56)	-73.70	3.74	OLS	0.93	OLS	83	11.13 **	0.50	20.27	56 Wool textiles
-17.46	(-0.39)	-0.39	0.24	OLS	1.48	OLS	83	12.45 **	0.53	21.98	57 Spinning and weaving
96.62	(0.96)	116.32	1.12	OLS	0.27	OLS	83	5.53 **	0.36	17.93	58 Hosiery and knitwear
-78.24	(-0.99)	-125.03	4.48	OLS	1.13	OLS	83	4.04 **	0.28	30.90	59 Textile consumer goods
-1.98	(-0.73)	-14.01	7.90	OLS	1.64	OLS	83	10.60 **	0.46	22.76	61 Footwear
17.35	(0.35)	-38.76	1.90	OLS	0.30	OLS	73	11.75 **	0.57	27.84	62 Leather and leather goods
14.42	(0.24)	16.66	3.20	OLS	1.10	OLS	83	7.58 **	0.44	0.37	63 Closing and fur
-13.70	(-0.35)	-112.37	13.82 *	IV	2.07 +	IV	83	10.49 **	0.40	23.88	64 Timber and wooden products other than furniture
-2.78	(-0.08)	27.40	12.09 *	IV	4.68 **	IV	83	7.80 **	0.24	25.65	65 Furniture, upholstery and bedding
-22.12	(-0.44)	59.06	1.96	OLS	0.40	OLS	83	4.77 **	0.16	32.86	66 Pulp, paper and board
-3.40	(-0.07)	-33.29	4.55	OLS	1.00	OLS	83	4.07 **	0.23	29.19	67 Paper and board products
105.82	(0.66)	-56.15	15.02 *	IV	4.55 *	IV	83	4.54 **	0.01	23.22	68 Printing and publishing

5.25	(0.14)	19.32	0.88		OLS	0.25	OLS	83	7.92	**	0.56	28.40	69 Rubber products
14.10	(0.17)	-74.24	11.07	*	IV	1.17	OLS	83	9.33	**	0.45	21.11	70 Plastic products

[a] Data set covers the period 1978 to 1999.

[b] ** = significant at 1 % level. * = significant at 5 % level. + =significant at 10 % level.

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Table 1: Estimation Results: Uncertainty (Entropy Measure) on Authorisation of Plant and Machinery

		(i) OLS		(ii) SURE	
Industry		*unc*	(t-value) [a]	*unc*	(t-value) [a]
22	Coal and petroleum product	0.65	(0.08)	-	-
23	Extraction of minerals and metalliferous	-1.07	(-0.51)	-	-
24	Ferrous metals	-0.70	(-0.50)	-1.25	(-1.28)
25	Non-ferrous metals	3.26	(0.45)	4.53	(0.78)
26	Building materials	4.23	(0.64)	1.30	(0.27)
27	Glass and ceramics	0.45	(0.18)	-0.43	(-0.26)
28	Industrial chemicals	4.97	(1.28)	5.30	(1.78) +
29	Agricultural chemicals	-0.45	(-0.86)	-	-
30	Pharmaceuticals and consumer chemica	-2.29	(-1.29)	-2.95	(-2.23) *
31	Man made fibres	34.38	(1.34)	-	-
32	Foundries; and forging, pressing and sta	3.61	(0.36)	-2.63	(-0.40)
33	Metals goods n.e.s.	1.25	(0.09)	-1.77	(-0.17)
34	Hand tools and implements	-3.40	(-0.54)	-	-
35	Constructional stealwork	-1.41	(-1.07)	-1.82	(-1.93) +
36	Heavy industrial plant	0.06	(0.06)	-0.39	(-0.53)
37	Agricultural machinery	-3.48	(-1.85) +	-5.28	(-3.89) **
38	Metal working machine tools	0.46	(0.17)	0.44	(0.23)
39	Engineer's small tools	31.42	(1.03)	57.46	(2.43) *
40	Industrial machinery	-1.33	(-0.18)	1.97	(0.38)
41	Contracters' plant	2.57	(0.73)	2.38	(0.91)
42	Industrial engines, pumps and compress	8.47	(1.20)	14.42	(3.15) **
43	Heating, ventilating and refregiating equ	-0.60	(-0.73)	-0.47	(-0.86)
44	Other mechanical equipment	-1.60	(-0.29)	0.51	(0.13)
45	Office machinery and data processing e	-1.21	(-1.65) +	-	-
46	Electrical industrial goods	0.90	(0.38)	2.07	(1.28)
47	Electronic industrial goods	0.63	(0.42)	0.70	(0.59)

Table 1: Estimation Results: Uncertainty (Entropy Measure) on Authorisation of Plant and Machinery (coninued)

Industry	*unc*	(t-value) [a]	*unc*	(t-value) [a]
48 Electrical consumer goods	-3.08	(-2.51) *	-	-
49 Electronic consumer goods	-0.01	(-0.004)	-	-
50 Motor vehicles	7.72	(0.62)	10.50	(1.13)
51 Shipbuilding	-0.71	(-1.04)	-	-
52 Aerospace and other vehicles	-0.03	(-0.01)	-1.59	(-0.40)
53 Instrument engineering	-0.41	(-0.28)	-0.97	(-0.96)
54 Food	-0.84	(-0.82)	-0.15	(-0.21)
55 Drink and Tabacco	-4.11	(-1.90) +	-2.75	(-1.81) +
56 Wool textiles	0.47	(0.98)	0.56	(1.50)
57 Spinning and weaving	-2.18	(-1.09)	-2.37	(-1.59)
58 Hosiery and knitwear	0.88	(0.15)	0.73	(0.16)
59 Textile consumer goods	0.70	(0.39)	1.54	(1.26)
61 Footwear	-0.39	(-0.14)	-1.85	(-0.10)
62 Leather and leather goods	0.61	(0.34)	-	-
63 Closing and fur	-1.23	(-0.63)	-2.24	(-1.59)
64 Timber and wooden products other than	0.89	(0.62)	0.59	(0.55)
65 Furniture, upholstery and bedding	-4.04	(-0.06)	-30.72	(-0.69)
66 Pulp, paper and board	-2.25	(-1.10)	-3.15	(-2.27) *
67 Paper and board products	-35.25	(-0.82)	-14.25	(-0.45)
68 Printing and publishing	-0.81	(-0.37)	-2.21	(-1.41)
69 Rubber products	-13.76	(-2.42) *	-14.77	(-3.91) **
70 Plastic products	-0.30	(-0.23)	-0.35	(-0.37)
Maximum	34.38	1.34	57.46	3.15
Median	-0.35	-0.10	-0.41	-0.24
Mean	0.45	-0.24	0.28	-0.28
Minimum	-35.25	-2.51	-30.72	-3.91

Note [a] ** = significant at 1 % level. * = significant at 5 % level. + =significant at Note [a] ** = significant at 1 % level. * = significant at 5 % level. + =significant at 10 % le

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Table 2: Estimations for Pooled Data (Homogeneous Estimators)[a]: Dep. Variable, Authorisation of Plant and Machinery based on CBI survey

	Explanatory Variables											
	Auth_1	(t-value)[b]	*Opt*	(t-value)	*Yfterm*	(t-value)	*Ybterm*	(t-value)	*Ybterm_1*	(t-value)	*Cuterm_1*	(t-value)
Case A: Uncertainty based on entropy measure (unc) and using all industries (panel data)												
Fixed Effects	0.35	(23.05) **	0.83	(9.21) **	0.17	(3.76) **	0.23	(5.42) **	0.18	(4.64) **	4.94	(2.92) **
Random Effects Model	0.38	(25.58) **	0.77	(8.78) **	0.19	(4.14) **	0.23	(5.62) **	0.18	(4.65) **	4.74	(2.97) **
Case B: Uncertainty based on entropy measure (unc) and where industries with negative and significant coefficients on unc are excluded												
Fixed Effects	0.35	(21.64) **	0.77	(8.32) **	0.16	(3.23) **	0.23	(5.44) **	0.18	(4.15) **	4.63	(2.59) *
Random Effects Model	0.38	(24.25) **	0.59	(7.95) **	0.15	(3.53) **	0.01	(3.53) **	0.01	(4.10) **	4.49	(2.64) **
Case C: Uncertainty based on entropy measure (unc) using all industries (Restricted SUR estimates)												
Restricted SUR	0.38	(25.90) **	0.85	(15.89) **	0.24	(6.41)	0.01	(7.96) **	0.01	(7.99) **	10.58	(7.47) **

Notes: [a] Coefficients are converted to Elasticity evaluated at mean. [b.] ** = significant at 1 % level. * = significant at 5 % level. + =significant at 10 % level.

[c.] F tests are carried out for Fixed-effects model, while Wald Chi Square Tests are for Random-effects model.

[d.] Housman Specification Test where the null is difference in coefficients of two models are not systematic.

[e.] Breusch and Pagan (1980) Lagrangian multiplier test for Random effects: Test for Var(u)=0, where ib[industry, t] =Xb + u[industry]+e[industry, t]

Table 2: Estimations for Pooled Data (Homogeneous Estimators)[a]: Dep. Variable, Authorisation of Plant and Machinery based on CBI survey (continued)

Uncertainty Measure									Joint Significant Tests				Speficication Tests	
Uncertainty Measure	(t-value)[b]		(t-value)	*Dlcu*	(t-value)	Cons	obs.	R2	F test / [c] Wald chi2	Time dummy	Industry dummy	Time & Industry	Hausman [d]	Breusch & Pagan [e]
Case A: Uncertainty based on entropy measure (unc) using all industries (panel data)														
-2.94	(-2.13) *	-	-	0.00	(-0.90)	-13.01	3798	0.48	35.24 **	2.61 **	-	-		
-2.57	(-1.96) *	-	-	0.00	(-0.81)	-2.29	3798	0.48	3463 **	200 **	45 **	241 **	119.33 *	10.91 *
Case B: Uncertainty based on entropy measure (unc) and where industries with negative and significant coefficients on unc are excluded														
0.56	(0.38)	-	-	-0.01	(-1.25)	-18.39	3427	0.48	32.26 **	2.57 **	-	-		
0.53	(0.44)	-	-	0.00	(-1.22)	-15.97	3427	0.49	3175 **	194 **	40 **	228 **	116.35 *	12.25 **
Case C: Uncertainty based on entropy measure (unc) using all industries (Restricted SUR estimates)														
-2.02	(-1.74) $^{+}$			-0.02	(-5.42) **	-	3192		2891.83 **					

Notes: [a] Coefficients are converted to Elasticity evaluated at mean. [b.] ** = significant at 1 % level. * = significant at 5 % level. $^{+}$ =significant at 10 % level.

[c.] F tests are carried out for Fixed-effects model, while Wald Chi Square Tests are for Random-effects model.

[d.] Housman Specification Test where the null is difference in coefficients of two models are not systematic.

[e.] Breusch and Pagan (1980) Lagrangian multiplier test for Random effects: Test for Var(u)=0, where ib[industry, t] =Xb + u[industry]+e[industry, t]

Table 3 : Comparison of Forecast Performance (RMSEs) across Industries (Entropy Measure (UNC) is used as one of the explanatory variables) [a]

	Not Pooled		*Pooled*			*SURE*		
Industry [b]	Case a): OLS based on the Individual Industry Data [d]	Case b): 2SLS based on the Individual Industry Data [d]	Case c): Fixed-effects Estimation [c] [d]	Case d): Random-effects Estimation [c] [d]	Case e): 2SLS based on the Pooled Data [d]	Case f): Restricted SURE Estimation [d]	Case g): Unrestricted SURE Estimation [d]	Case h): Restricted SURE : Coef of Cu_1 set to be equal across industries [d]
24 Ferrous metals	35.65	40.80	37.69 **	35.73 *	33.33	38.40 *	36.59	40.07 *
25 Non-ferrous metals	35.17	50.95 *	27.37	34.87	35.58 *	35.14	30.63	32.24
26 Building materials	20.04	21.38	18.32	21.00	19.22	19.33	20.07	21.27
27 Glass and ceramics	22.43	23.64	18.64	18.69	19.51	19.61	21.64	22.50
28 Industrial chemicals	23.44	23.23	20.06	22.45	23.81	23.28	27.05	29.16
30 Pharmaceuticals/consumer chemicals	16.94	29.59	12.22	21.37	19.06	20.35	16.89	16.76
32 Foundries; /forging, pressing & stampir	27.38	35.58	24.28	25.58	28.39	25.50	29.55	29.68
33 Metals goods n.e.s.	24.40	25.04	22.52	18.44	20.84	19.93	25.48	25.49
35 Constructional stealwork	19.78	18.14	21.40	18.72	22.21	19.20	20.32	21.17
36 Heavy industrial plant	21.83	25.82	18.54	13.92	18.64	15.47	20.55	21.04
37 Agricultural machinery	55.32 **	57.41 **	39.77 **	39.76 **	39.04 **	44.76 **	62.32 **	51.41 **
38 Metal working machine tools	15.59	22.99	22.84	14.93	17.25	17.38	15.30	15.96
39 Engineer's small tools	16.71	17.77	21.39	17.58	16.87	17.65	17.07	16.11
40 Industrial machinery	33.46	27.79	29.43 *	30.32	28.92	30.37	34.09	32.62
41 Contracters' plant	31.17	28.65	22.35	28.13	30.15	28.73	32.09	30.74
42 Industrial engines, pumps & compress	24.66	38.89	22.01	19.84	21.23	23.55	25.96	26.12
43 Heating, ventilating & refregiating equip	25.24	26.06	19.57	29.50	26.62	24.68	24.76	24.25
44 Other mechanical equipment	15.33	17.86	17.10	14.91	15.18	14.78	15.11	14.95
46 Electrical industrial goods	29.33	24.06	26.64	25.00	24.72	27.74	28.94	30.29
47 Electronic industrial goods	32.98	31.56	24.92	27.36	30.50	28.95	32.82	33.39
50 Motor vehicles	25.89	29.43	21.49	22.07	18.57	25.16	26.06	25.30
52 Aerospace and other vehicles	61.78 **	90.49 **	29.25 **	61.76 **	65.69 **	65.02 **	61.42 **	62.28 **
53 Instrument engineering	34.48	34.75	17.16	30.07	30.76	29.58	35.16	34.20
54 Food	18.10	25.57	13.19	16.70	17.48	17.06	18.85	19.17
55 Drink and Tabacco	37.66 *	40.29	20.33	37.08 *	35.72 *	37.94 *	42.67 *	43.17 *
56 Wool textiles	26.44	30.32	30.57 **	22.36	23.01	23.85	27.03	27.54
57 Spinning and weaving	29.30	33.08	22.66	27.03	26.43	25.26	26.36	24.68

58 Hosiery and knitwear	27.71	37.10	20.35	26.12	24.31	25.30	28.49	28.82

Table 3 : Comparison of Forecast Performance across Industries (Entropy Measure is used as one of the explanatory variables) [a] (Continued)

	Not Pooled		*Pooled*			*SURE*		
Industry [b]	Case a): OLS based on the Individual Industry Data [d]	Case b): 2SLS based on the Individual Industry Data [d]	Case c): Fixed-effects Estimation [c] [d]	Case d): Random-effects Estimation [c] [d]	Case e): 2SLS based on the Pooled Data [d]	Case f): Restricted SURE Estimation [d]	Case g): Unrestricted SURE Estimation [d]	Case h): Restricted SURE : Coef of Cu_1 set to be equal across industries [d]
59 Textile consumer goods	44.25 **	59.54 **	26.05	37.62 **	36.97 **	39.03 **	47.41 **	47.00 **
61 Footwear	24.64	30.33	24.50	22.15	24.52	24.17	25.04	24.49
63 Closing and fur	37.89 *	47.83 *	21.34	30.29	30.18	30.82	39.67 **	33.48 **
64 Timber and wooden products other tha	19.65	25.06	13.58	16.81	17.64	17.43	19.60	19.18
65 Furniture, upholstery and bedding	29.44	26.44	17.52	21.70	22.81	23.40	27.91	28.00
66 Pulp, paper and board	23.46	29.07	18.82	25.07	25.71	25.19	21.97	22.67
67 Paper and board products	28.40	34.18	25.88	28.05	28.32	28.48	28.80	29.13
68 Printing and publishing	25.51	29.54	13.75	22.24	24.46	24.38	25.25	23.22
69 Rubber products	32.57	43.24	24.55	30.86	30.42	34.96	34.35	35.60
70 Plastic products	14.62	24.61	15.10	23.97	26.15	25.67	27.35	26.29
RMSEs: Mean across Industries	28.12	33.11	22.19	25.79	26.32	26.78	28.96	28.67
(Rank among Cases (a)-(h))	(5)	(8)	(1)	(2)	(3)	(4)	(7)	(6)

Notes [a] Out-of-sample forecast is made based on the truncated data set without last three years (i.e., 12 quarters).
Then, the RMSEs (the root mean square errors) at the industry level are calculated and averaged across industries.

[b] The Industries with missing variables are dropped to make the comrapison between different estimators feasible.

[c] Only the cases where both time and industry dummy variables are included are presented.
RMSEs in the cases where none or either time or industry variables are included are slightly larger than these cases.

[d] ** denotes the top three industries and * denotes top four and five industries in terms of forecast error.